World Academy of Science, Engineering and Technology
International Journal of Industrial and Systems Engineering
Vol:16, No:4, 2022

Networked Implementation of Milling Stability Optimization with Bayesian Learning

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Open Science Index, Industrial and Systems Engineering Vol:16, No:4, 2022 publications.waset.org/10012516.pdf

***Abstract*—**Machining instability, or chatter, can impose an important limitation to discrete part machining. In this work, a networked implementation of milling stability optimization with Bayesian learning is presented. The milling process was monitored with a wireless sensory tool holder instrumented with an accelerometer at the TU Wien, Vienna, Austria. The recorded data from a milling test cut were used to classify the cut as stable or unstable based on a frequency analysis. The test cut result was used in a Bayesian stability learning algorithm at the University of Tennessee, Knoxville, Tennessee, USA. The algorithm calculated the probability of stability as a function of axial depth of cut and spindle speed based on the test result and recommended parameters for the next test cut. The iterative process between two transatlantic locations was repeated until convergence to a stable optimal process parameter set was achieved.

***Keywords*—**Bayesian learning, instrumented tool holder, machining stability, optimization strategy.

I. Introduction

MACHINING stability is an important factor for high process efficiency. Thus, this topic has been well investigated and described by theoretical models for the past few decades [1]–[3]. Nevertheless, gaining knowledge of the modal parameters is necessary to calculate the stability lobe diagrams [4]. Showing the parameter combinations of spindle speed and cutting depth affecting the chatter stability [4], [5], these diagrams can alternatively be created using a set of experimental points obtained from multiple cutting tests [6]. Both prior investigation of modal parameters obtained by modal hammer testing [7] and time-consuming investigation of many experiments require significant effort in time and equipment.

Integrated sensors provide a broad portfolio for process monitoring and control [8]. In this paper, an industrially applicable solution is presented which implements a networked small set of experiments monitored with an instrumented tool holder [9]-[11] by the TU Wien. The recorded signals were evaluated in real time using a Bayesian stability learning algorithm [4], [12] at the University of Tennessee, Knoxville, Tennessee, USA.

II. Experimental Setup

The iterative procedure consisted of the machining tests performed in Vienna, Austria, online data evaluation for categorization of the recent result, and Bayesian updating in Knoxville, TN, USA, that recommended the parameters for the following cut. As an uninformative prior was chosen for the process, no pre-testing characterization by modal analysis or simulations was required [12].

A. Test Setup with Instrumented Tool Holder

Milling tests were performed on a DMG MORI DMU 75 monoblock CNC machining center using an aluminum EN AW-6060 T66 workpiece. Machining tests were completed along a 120 mm straight path using a 10 mm diameter solid carbide end mill with four equally-spaced flutes for down milling. The radial immersion was 20% and the feed per tooth was 0.1 mm. The range of axial depth of cut and spindle speed for testing was 0 mm to 8 mm and 5000 rpm to 9000 rpm, respectively. External flood cooling was used and the process was monitored by an instrumented tool holder, as depicted in Fig. 1.

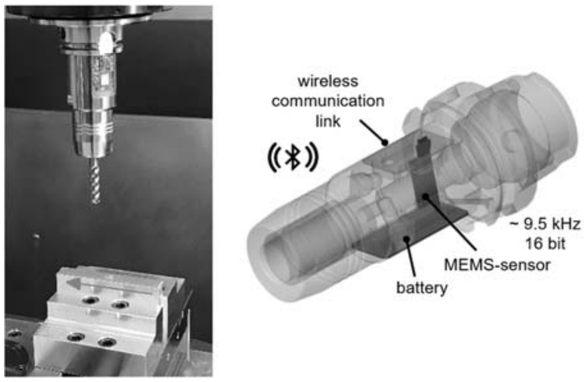

Fig. 1 Milling test setup with instrumented tool holder

B. Online Data Evaluation

The data recorded by the instrumented tool holder were used to classify the individual test cuts as stable or unstable using the

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This manuscript has been authored in part by UT-Battelle, LLC under Contract No. DE-AC05-00OR22725 with the U.S. Department of Energy. The United States Government retains and the publisher, by accepting the article for publication, acknowledges that the United States Government retains a non-exclusive, paid-up, irrevocable, world-wide license to publish or reproduce the published form of this manuscript, or allow others to do so, for United States Government purposes. The Department of Energy will provide public access to these results of federally sponsored research in accordance with the DOE Public Access Plan (http://energy.gov/downloads/doe-public-access-plan).

frequency content. Due to the rotation of the tool holder, a modulation can be seen on each frequency component of the sensor's signal compared to a stationary sensor that might be placed, e.g., on the workpiece or machine. Nevertheless, a distinction is possible, whether a certain frequency comes along with pure rotation and regular cutting, or if chatter occurred with frequencies that do not fit this pattern of regular motion. In Fig. 2 the spectra of a stable and an unstable cut are shown for comparison. For the end mills with four cutting teeth, in a stable process, the main frequencies occur in a narrow area around the odd numbers of the multiples of the rotational frequency (gray background), due to the frequency modulation due to a rotating sensor [10]. It can be seen that in the case of chatter, certain frequencies occur besides the pure odd numbered multiples of the rotational frequency.

For the chatter classification a ratio value was used, dividing the maximum amplitudes of the components in between the odd-numbered multiple by the sum of amplitudes at the odd-numbered multiples. Using this procedure, it is possible to calculate a stability value out of the time series using a rolling window function (length 0.2 s, 20 samples steps) for the frequency spectrum online. If this ratio exceeds a specified limit, the cut is classified as unstable. Through this procedure, the stability of the process was determined and classified.

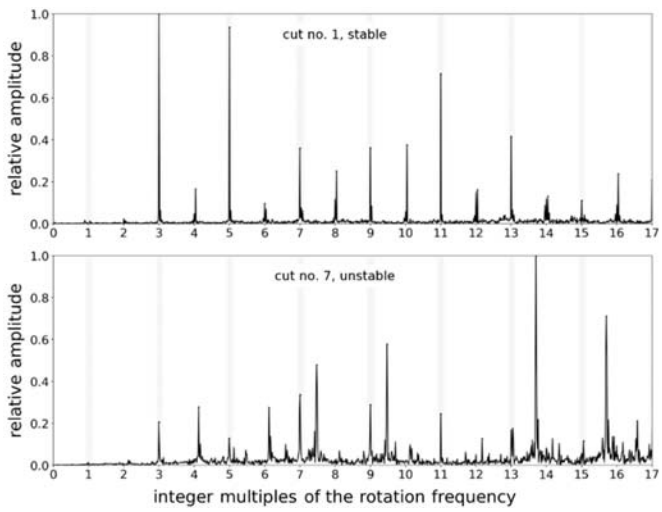

Fig. 2 Spectra of cut no. 1 (top, classified as stable) and of cut no. 7 (bottom, classified as unstable)

C. Bayesian Updating and Derived Set of Parameters

The Bayesian learning approach updates the probability of stability stepwise with the number of cuts performed. Discretizing the axial depth and spindle speed range into grid points and assigning an initial probability of stability to each grid point is required at the beginning. If the frequency response function is unknown, a basic assumption for linear decrease in the probability of stability with cutting depth is made for the prior probability of stability [12].

Based on the online-evaluation and classification of the instrumented tool holder's data, the next set of parameters (cutting depth and spindle speed) was chosen using the probability of stability and expected percentage improvement in material removal rate as the selection criterion [12]. The classification of the previous cut supported the automated decision-making of the algorithm for choosing the next data set. The sequence of test cuts and the updated probability map after the first test is shown in Fig. 3. In detail Fig. 3 (a) shows the prior probability of stability; the prior probability of stability is taken to decrease linearly from 1 at 0.01 mm to 0.01 at 8 mm. The optimal parameter before any testing is completed is 9000 rpm, 0.01 mm. The expected percent improvement in material removal rate is shown in Fig. 3 (b). The optimal test parameters are 9000 rpm, 4 mm (highlighted by the arrow). The test was completed and determined to be stable.

Fig. 3 (c) shows the updated probability of stability given the stable result at 9000 rpm, 4 mm. Fig. 3 (d) displays the expected percent improvement in material removal rate for the second test. The optimal parameters for the second test are 9000 rpm, 5.2 mm. Table I shows the results from the test procedure. The testing was terminated when the expected percent improvement in material removal rate was less than 1%.

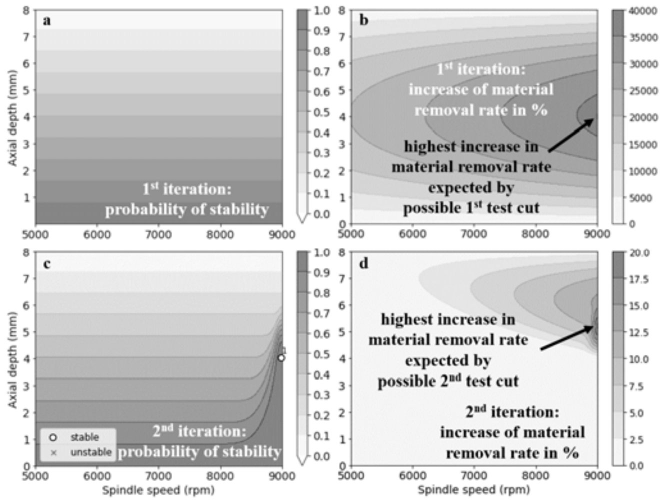

Fig. 3 Probability of stability and expected percent improvement in material removal rate for test 1 and test 2

TABLE I
SET OF PARAMETERS

Number of test cut	Spindle speed in revolutions per minute	Axial depth of cut in mm	Expected increase of material removal rate in %	Resulting behavior
1	9000	4	36309.5	stable
2	9000	5.2	18.9	stable
3	9000	6.1	11.5	unstable
4	9000	5.5	3.9	stable
5	9000	5.9	5.0	unstable
6	8510	6.9	2.6	unstable
7	8170	7	2.0	unstable
8	8700	6.3	1.5	stable
9	8700	6.7	3.9	stable
10	8700	7.2	4.9	unstable
11	8710	6.9	1.3	unstable

III. RESULTS

As shown in Table I, an optimum set of parameters was

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found within only 11 tests. Furthermore, the recorded data were investigated to highlight differences between stable and unstable sets of data.

A. Optimized Machining Parameters

The final stability diagram is depicted in Fig. 4 and shows the probability of stability in grey scales. Note that the most important area for improving material removal rate is located at high spindle speed and axial depth combinations. Therefore, the algorithm investigates the right upper corner closely; this is shown in the expected improvement in material removal rate plot in Fig. 4 (b), which identified the expected improvement in material removal rate for the 12th test run which was not completed. As seen in Fig. 4 (a), there is convergence to the optimal stable parameters.

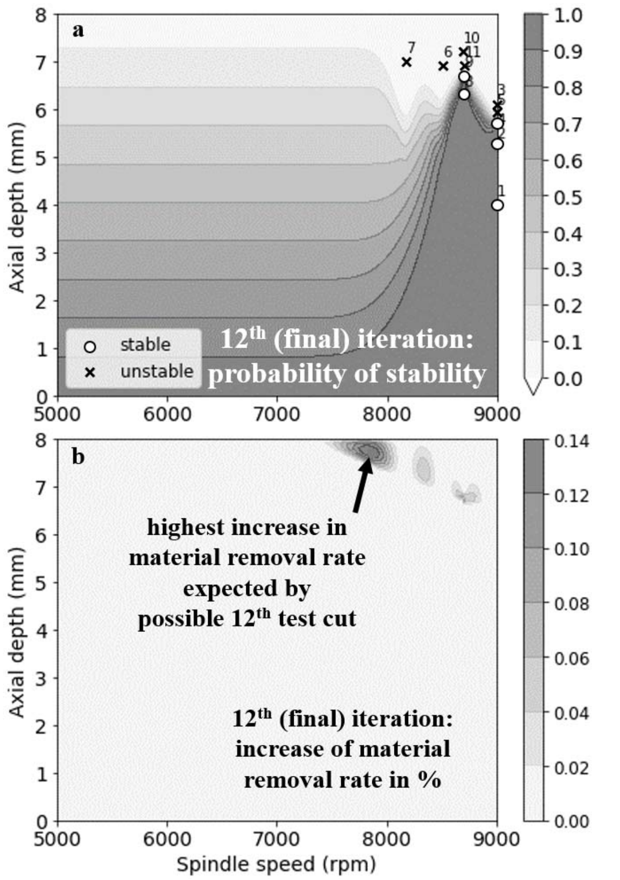

Fig. 4 Probability of stability map (top), and expected increase in material removal rate (bottom), both after 11th test cut

B. Stability Estimation Based on Autocorrelation

In the post-processing, further data analysis methods have been applied. For processes with high periodicity, autocorrelation can be used to quantify self-similarity. To illustrate the periodicity, the signal is depicted in form of a polar plot for this effort. Here, the measured acceleration signal of each spindle revolution is displayed on the diagram between 0 and 360 degrees. This results in an angle-dependent representation of the acceleration. If the cut is stable, the acceleration is repeated very reliably from revolution to revolution, leading to a high autocorrelation; see Fig. 5.

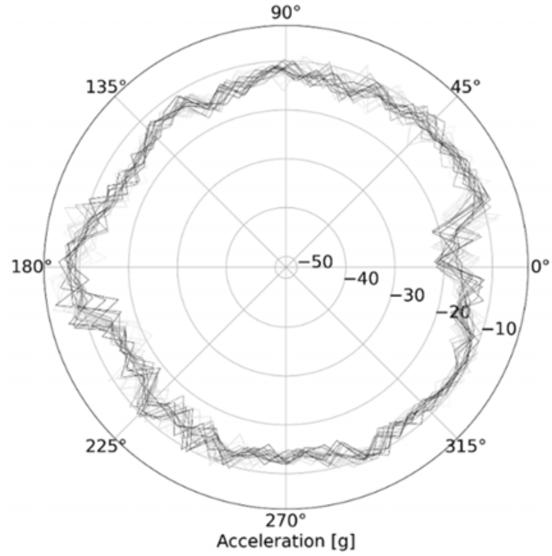

Fig. 5 Polar plot of cut no. 4 (stable)

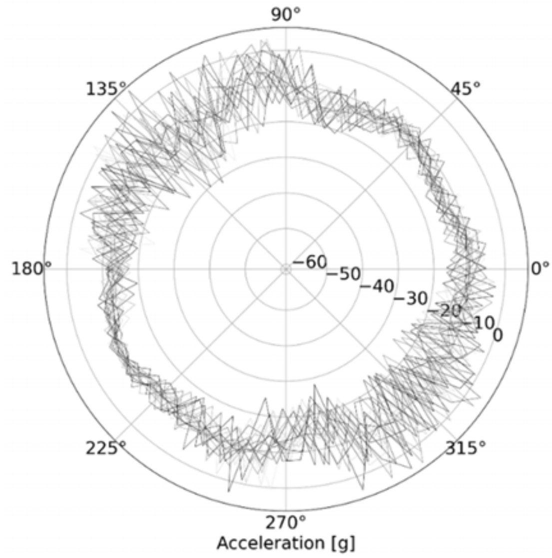

Fig. 6 Polar plot of cut no. 6 (unstable)

If, on the other hand, the cut is unstable, there is no good correlation of the acceleration signal from revolution to revolution. This case is shown in Fig. 6, where no recurring acceleration deflections are evident and the self-similarity of the signal is very low. Due to the chatter vibrations that occur, a further excitation that is not, in general, a multiple of the periodic tooth passing frequency is superimposed on the vibrations caused by the cutting process. This leads to the variable acceleration in the process and a decreasing self-similarity. Based on this circumstance, it is possible to calculate the autocorrelation of the acceleration signal of the individual revolutions with each other. Here, a better correlation is obtained for the stable than for the unstable cut.

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C. Effects on Surface Quality

Further evaluation of the test cut stability can be completed using the surfaces produced by the milling process. For this purpose, the produced surfaces of all the cuts were saved and measured. An example of a surface created by an unstable cut is shown in Fig. 7. The chatter marks are a result of the superimposition of chatter vibration on regular cutting conditions. The chatter marks form deep grooves over the entire axial depth of cut and reduces the surface integrity. The chatter marks are visible in Fig. 7 and increase the surface roughness.

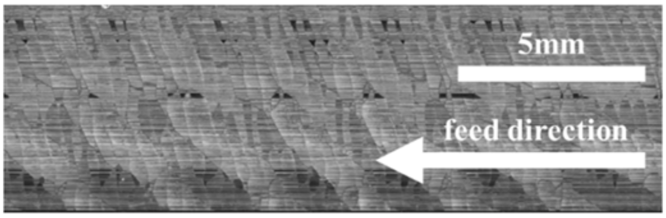

Fig. 7 Section of the surface of cut no. 5 with chatter marks

IV. Conclusion and Outlook

The combination of an instrumented tool holder and Bayesian updating was successfully demonstrated for iteratively identifying an optimum set of stable parameters for milling. Taking chatter and material removal rate into concern, the procedure was able to optimize a setup without any prior frequency response function measurements or cutting force model identification.

Online data analysis was focused on the frequency content of the signals to distinguish between stable and unstable conditions. Additionally, post-processing highlighted other signal characteristics, including autocorrelation and self-similarity in polar plots.

The fast and easy setup and the self-adjusting algorithm can be used within an autonomous testing procedure. Therefore, an optimized material removal rate can be found for different scenarios even in highly automated machining cells.

Future work includes a justification regarding the intensity and exact frequency content of chatter will be implemented to advance the algorithm. This would enable quantifying stability more than as a binary criterion (stable, unstable). In addition, the machined surface finish may be taken into account for stability classification.

Acknowledgment

The authors want to express appreciation and thanks to the Austrian Marshall Plan Foundation for supporting the research work and strengthening the academic exchange between TU Wien and US universities.

On the US side, this research was supported by the DOE Office of Energy Efficiency and Renewable Energy (EERE), Energy and Transportation Science Division, and used resources at the Manufacturing Demonstration Facility, a DOE-EERE User Facility at Oak Ridge National Laboratory.

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